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Multivariate time-series blood donation/demand forecasting for resilient supply chain management during COVID-19 pandemic

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ABSTRACT

COVID-19 has caused negative impacts on blood supply chain management, due to uncertain supply/demand and logistical disruptions. In the early weeks following the COVID-19 pandemic, 20–30% reduction in blood donation had observed, which adversely affected the whole blood supply chain. Although this shortage was partially compensated through rescheduling of elective surgeries and shifting some inpatient surgeries to outpatient surgeries, resumption of the normal surgeries by hospitals had increased the demands for the blood products. At the same time, the total blood supply was increased by some measures taken to overcome the blood shortage. In this paper, a multivariate time-series deep learning model based on long short-term memory is proposed to forecast the blood donation/demand. It takes daily time-series of blood donation/demand (internal features) as well as daily time-series of new confirmed COVID-19 cases/deaths (external features) as its inputs, and predicts blood donation/demand for the next week. The proposed model is used to achieve a resilient blood inventory management, capable of handling the uncertainties occurring during the COVID-19 pandemic. The proposed blood donation/demand forecasting model has been successfully simulated on the collected data of Tehran Blood Center in Tehran, Iran, for a time period from February 24, 2020, to October 14, 2021. Obtained results show the efficiency of the proposed model by obtaining 6.1% and 6.5% error between the actual and forecasted values of the number of donations and demands, respectively. The results of applying the proposed model for inventory management of blood platelets demonstrate the resiliency of our model to reduce shortage and wastage rates against the existing uncertainty handling models by 32.1% and 26.6%, respectively. The proposed method can be used to assist the decision makers in managing the blood supply chains through prioritizing the blood transfusions during COVID-19 and similar pandemics in the future.

1. Introduction

Coronavirus disease 2019 (COVID-19) was firstly detected in Wuhan, China, in December 2019, and then, in February 2020, large spreads were observed in Lombardy, Italy, and Qom, Iran (Ghafari et al., 2021). It was announced by world health organization (WHO) as a global pandemic on March 11, 2020 (Shokouhifar and Pilevari, 2022). By outbreaking the COVID-19 pandemic in the world, many countries had performed some lockdowns especially at the early epidemic peaks (Pilevari et al., 2021; Zahraee et al., 2022). The COVID-19 pandemic has imposed new challenges to the healthcare delivery (Senapati et al., 2021). Diversion of the healthcare staff towards the care of the COVID-19 patients, difficulties in commuting to hospitals and reduced services to inpatients and outpatients to ensure physical distancing, had led to significant obstacles for the non-COVID patients (Dore, 2020).

The COVID-19 outbreak has caused a significant drop in blood supply by affecting the donor attendance, which has negatively affected the blood supply chain (BSC) management (Halawani, 2022). Inventory management in BSC has become more difficult recently, due to the effects of the COVID-19 pandemic. The main supplier of the blood products is voluntary donors, and thus, unavailability of donors during the COVID-19 peaks is a major challenge (Balagholi et al., 2021). Based on the WHO reports, outbreaking the COVID-19 pandemic had led to reduce the total blood supply around 20 % to 30 % in different regions (Loua et al., 2021). Although this shortage was partially compensated by reducing the demand for blood products through rescheduling of elective surgeries and shifting some inpatient surgeries to outpatient surgeries (Stanworth et al., 2020), maintaining a proper balance between

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production and demand during different stages of the COVID-19 pandemic remains a challenge.

To manage the healthcare supply chain, prediction of the blood supply/demand is critical, as blood plays an essential role in saving lives (Mohammadi et al., 2022). Forecasting of the blood supply and demand is critical to make right decisions in terms of the donation units, transportation schedule, and inventory management. In the case of the blood platelets with very short shelf-life of five days (Sohrabi et al., 2021a), it is of utmost importance to properly forecast the supply/demand, in order to reduce both shortages and wastages (Rajendran and Ravindran, 2019). Predicting the need for blood platelets during the different stages of the COVID-19 pandemic is a challenging task due to the intense changes in the health situation and behavior of donors (Gupta et al., 2021).

Recently, machine learning techniques have been applied to tackle the COVID-19 in three phases: screening, medical aid, and forecasting (Shahid et al., 2021; Al-Qaness et al., 2021a). The main focus of the forecasting methods is to predict next pandemic peaks (Ayoobi et al., 2021; Kumar and Susan, 2021). To support the COVID-19 response, these models can be used to improve the healthcare supply chains based on the changes in the uncertain environment related to the COVID-19 pandemic (Torrado & Barbosa-Póvoa, 2022). Although supply and demand uncertainties were handled in previous studies as stochastic, forecasting, and fuzzy (Sohrabi et al., 2021b), prediction of the blood donation and demands considering the new COVID-19 cases/deaths remains a challenging task.

To overcome the mentioned drawbacks in handling supply/demand uncertainties in BSC management, we propose a multivariate time-series model to efficiently forecast the blood supply/demand utilizing multiple historical time-series. The proposed model takes time-series of the blood donation/demand and new confirmed COVID-19 cases and deaths as its inputs, and forecasts the blood donation/demand for the next week. Accordingly, the inventory of the blood platelets can be more efficiently managed based on the predicted blood supply/demand. Our motivation is to more realistically manage the BSC and assist the BSC decision maker to adopt more sustainable decisions, resulting a better trade-off between the blood shortage and wastage.

This paper contributes to the literature in the following aspects:

- Introducing a multivariate time-series model based on long short-term memory (LSTM) for the blood donation/demand forecasting during the COVID-19 pandemic.
- Multivariate time-series blood donation/demand forecasting not only on the basis of the past values of the donation/demand (internal features), but also using the time-series of new confirmed COVID-19 cases and deaths (external features).
- Achieving a resilient blood supply chain management during COVID-19, capable of efficiently handling the uncertainties occurring in the blood supply/demand.
- Utilizing the proposed model for the forecasting and inventory management of blood platelets on the collected data of Tehran Blood Center in Iran from February 24, 2020, to October 14, 2021.

The reminder of this paper is organized as follows: Section 2 reviews the challenges of the inventory management of blood products related to the COVID-19 pandemic. The proposed blood donation/demand forecasting model is discussed in Section 3. The collected data of blood donation, blood demand, and COVID-19 cases and deaths, and the results of the proposed model are provided in Section 4. Finally, the paper would be concluded in Section 5.

2. Potential challenges during COVID-19 pandemic

There are different challenges during the COVID-19 crisis, which affected the BSC management. The COVID-19 pandemic not only had negative impacts on the nodes (members) of a supply chain, but also affected its edges (ties) (Gunessee and Subramanian, 2020) which results in significant disruptions in the flow of the supply chain. In the following, potential challenges of the BSC management during the COVID-19 pandemic related to the supply, demand, safety rules, elective surgeries, and inventory management, are discussed.

2.1. Challenges related to supply

By outbreaking the COVID-19 pandemic, significant shortages in the blood supply were observed around the world, mainly due to the lockdowns, panic, suspension of the donation camps, and disruptions in the transportation services during the pandemic (Tan et al., 2021a). The donors were selected more stringent, which further decreases the number of donations (NBTC, 2020). Moreover, avoiding public gathering and maintaining social distancing are the main non-pharmacological factors which had led to significant drops in blood donation drives. Based on the reports of WHO, outbreaking the COVID-19 pandemic reduced the total blood supply by approximately 20–30 % in the different regions. For instance, the number of blood donations has dropped by 10–30 % in Washington, USA, and by 30 % in Canada (Loua et al., 2021). In the early weeks following the pandemic, the USA blood centers reported a significant drop in the total blood supply. Moreover, blood drives were continued to be repealed, as many schools, universities, and businesses remained closed (AABB, 2020a). Because of the same reasons, the national blood center in Malaysia reported a 40 % reduction in the donor attendance, compared with the same time periods in the previous years (TheStar, 2020). At the beginning of the COVID-19 outbreak, the total blood supply in had dropped by 67 % Zhejiang, China (Wang et al., 2020), and by 10 % in Italy (Franchini et al., 2020).

2.2. Challenges related to demand

At the beginning of the COVID-19 pandemic, governments forced hospitals to treat only emergency and COVID-19 patients, which had led to postpone elective transfusions (MoHFW, 2020). Admission of most non-COVID-19 patients and elective surgeries were cancelled, to avoid further spread of COVID-19 (Maghsudlu et al., 2021). By adopting these rules, the above-mentioned shortage was partially compensated through the reduction in the demand for the blood products, and consequently, the inventory of the blood products remained in an acceptable level (Stanworth et al., 2020). Analyzing two periods of 30 days before and during the lockdown (starting on March 25, 2020) in an oncology center in India shows that 1507 patients were admitted in the pre-lockdown 30-day period, whereas only 432 patients were admitted during the 30-day period following the lockdown (Ojha et al., 2020).

2.3. Challenges related to safety

In an effort to maintain the blood inventory, safety of the donors and staffs cannot be jeopardised. The blood collection sites need more disinfection, and medical wastage disposals should be handled more meticulously (Arcot et al., 2020). Traditionally, a blood donor should satisfy various requirements range from the background conditions (e.g., sexual, medical, and travel history) to the physical conditions (e.g., age, weight, and blood pressure) (Ngo et al., 2020). By outbreaking the COVID-19 pandemic, blood centers and blood drives have adopted additional screening requirements to prevent further spread of the pandemic. For example, these measures in USA include temperature screening, sanitizing hands, wearing face masks, social distancing, disinfecting machines and surfaces before each donation. In addition, it has to be mandated to the donors to inform the blood bank in the cases they develop any symptoms of COVID-19 within two weeks of donation (NBTC, 2020). By adopting these policies, the number of blood donors were reduced and more blood drives were cancelled, especially at the epidemic peaks (AABB, 2020b).

2.4. Challenges related to elective surgeries

By the COVID-19 outbreak, hospitals were recommended to reschedule elective surgeries and shift elective urgent inpatient surgeries to outpatient surgeries (CDCP, 2020). These policies were initiated by many hospitals on March 2020. For example, Washington Medical Center in USA started elective surgeries and postponed some surgeries from March 7, 2020, and reached parity blood usages and demands (Pagano et al., 2020). As seen in Fig. 1, 25 % of hospitals in USA reported increased blood wastage on the week of April 1, due to electively cancelled surgeries and nonurgent medical procedures. This wastage rate gradually increased until reaching a peak at the week of May 6 by 54 % of the hospitals. Then, in the week of May 13, the wastage rate was reduced to 52 %, as some hospitals resumed their elective surgeries (AABB, 2020c). Although the demand significantly decreased by postponing elective surgeries at early COVID-19 pandemic, great shortages observed as most hospitals resumed elective surgeries and increased non-COVID-19 admissions. Furthermore, due to 14-day incubation period of the positive cases and asymptomatic carriers, enlisting blood donors and maintaining safety in the donation procedure remain major concerns. Therefore, long-term blood shortages may be observed during the pandemic peaks (Ngo et al., 2020).

2.5. Challenges related to inventory management

Blood platelets have a very short shelf-life of 5 days (Fung et al., 2017). It causes serious challenges for the hospitals to maintain the required inventory of the blood platelets which minimizes both wastage and shortage (Tan et al., 2021b). As mentioned above, by spreading the COVID-19 pandemic, blood centers faced a decrease in the number of donors, and blood drives continued to be cancelled. To compensated this shortage in the blood supply, some measures have been taken by the blood centers and hospitals, which varied from a country (or a blood center) to another. For example, the measures taken in early weeks following the pandemic in China, Iran, and Italy, are summarized in Table 1. Generally, these measures can be categorized into two groups (Al-Mahmasani et al., 2021):

- *Measures taken to limit the spread of the virus*. The most common measures taken to reduce the spread of the virus include wearing face masks, temperature screening, ensuring social distancing, and screening the donors to be free of the COVID-19 symptoms or exposure to the COVID-19 patients. Moreover, some policies have been taken by hospitals to postpone elective surgeries.
- *Measures taken to reduce the blood shortage*. To compensate the shortage in the blood products, more mobile blood drives have been applied, and different measures have been adopted to encourage the blood donors via traditional media and social media, about the requirement, security, and safety of the blood donation procedure. Moreover, in some countries, an online system has been created to show the real-time inventory of all blood centers, whereby in the case of shortage in a center, its neighbors are asked for the blood units.

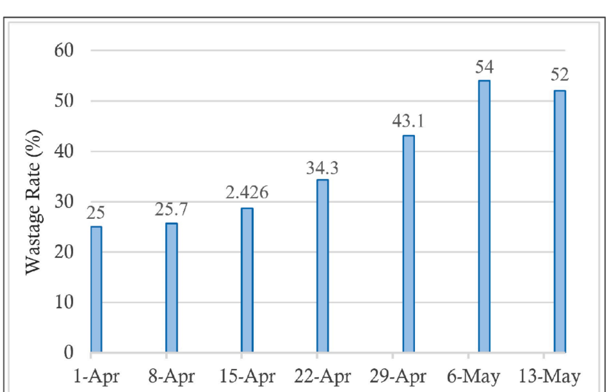

Fig. 1. Increasement in wastage rate due to postpone elective surgical cases in USA from April 1, 2020, to May 13, 2020.

Table 1
Measures taken to compensate the shortage of the blood products in China, Iran, and Italy, during COVID-19.

Country	Measures taken
China	Pleading the public for the blood donation, instead of having volunteer donors at blood drives
	Recruiting donors through traditional and social media
	Providing donors with information about COVID-19 before taking appointments to donate blood
	Deferring blood donations from donors traveling from, or residing in, the regions hardest hit by COVID-19
	Performing pre-donation screening (e.g., temperature check and physical exam)
	Thoroughly cleaning and disinfecting all sites of blood donation
	Providing full equipment and protection gear to laboratory staff
Iran	Creating online system for coordination among blood centers
	Ensuring enough personal protective equipment for employees and donors
	Changing the style of waiting line chairs at donation sites
	Increasing disinfection of all the contacting surfaces
	Decreasing waiting time through an online ticketing system
	Increasing working hours of donation centers and removing weekend holidays
Italy	Reorganizing hospital activities
	Running national media campaigns to increase awareness on blood donation
	Deferring blood donors who have fever, symptoms of respiratory tract infection, or who have had any contact with a suspected or confirmed COVID-19 case within the past two weeks of donation

Comparison of the blood donation and demand before and during the COVID-19 pandemic in some countries/regions are provided in Table 2. Based on the reported data from September 2019 to May 2020 in King Abdullah Hospital (Yahia, 2020), Saudi Arabia, 39.5 % drop in the blood donation and 21.7 % drop in the blood demand had been observed after outbreaking of the COVID-19 pandemic in Saudi Arabia. According to the collected data from 37 countries in WHO African Region (Loua et al., 2021), the blood supply reduction rate in 32 countries varied from 0.07 % to 44.2 % over the first 5 months of 2020 compared to the first 5 months of 2019, while an increasement up to 14 % has been reported in 5 countries over the same period. Moreover, the demand for the blood transfusion dropped by 8.3 % for red blood cell, 14.9 % for platelets, and 3.5 % for fresh frozen plasma, over the first 5 months of 2020 compared to the first 5 months of 2019. In Raja Permaisuri Hospital, India, totally 14,486 blood bags had been collected from March 2019 to August 2019, whilst the number of collected blood bags has reduced to 11,895 during the same period in 2020, which shows 17.9 % drop in the total blood supply. Moreover, 20.6 % drop in the total demand had been observed over the same period in 2020, mainly due to reduction in the elective cases.

2.6. Time-series forecasting techniques

Time-series forecasting has various industrial and scientific applications in logistics, predictive maintenance, healthcare, climate science, etc. Although classical techniques such as autoregressive integrated moving average (ARIMA) may achieve good results, machine learning is known as an attractive option to improve the efficiency of the prediction model especially in large-scale datasets with higher dimensionalities (Herzen et al., 2022). Al-Qaness et al. (2021b) proposed a time-series model for air qualify index forecasting using a modified adaptive neuro-fuzzy inference system (ANFIS) and a hybrid optimization technique based on particle swarm optimization (PSO) and slime mould

Table 2
Comparison of the change in blood donation and demand before and during COVID-19.

Ref.	Country/Region	Hospital	Number of blood donation			Number of blood unit demand		
			2019	2020	Change %	2019	2020	Change %
Balagholi et al. (2021)	Iran	Tehran Center	78,326	62,026	−20.8	N/A	N/A	N/A
Loua et al. (2021)	WHO African Region	N/A	1,800,236	1,498,773	−16.7	1,683,345	1,471,088	−12.6
Tan et al. (2021b)	India	Raja Permaisuri	14,486	11,895	−17.9	9,936	7,888	−20.6
Yahia (2020)	Saudi Arabia	King Abdullah	293	175	−39.5	313	245	−21.7

algorithm (SMA). Sadeghi et al. (2021) presented a combined time-series model based on multi-class support vector machine (SVM) and fuzzy genetic algorithm for the trend forecasting in Forex markets. Al-Qaness et al. (2022a) developed a marine predator algorithm with additional mutation operators (named MPAmu) to improve ANFIS in estimating wind power using time-series datasets from wind turbines located in France. Moreover, a combined metaheuristic-machine learning method based on aquila optimizer opposition-based learning and ANFIS, named AOOBL-ANFIS, has been used for the oil production forecasting (Al-Qaness et al., 2022b).

Multivariate time-series prediction techniques are also presented in literature. Liu et al. (2021) developed a deep learning architecture, termed as Deep Traffic State Prediction (DeepTSP), to handle the challenge of data scale, granularity, and sparsity in large-scale traffic state prediction systems. They not only utilized internal information (historical data of traffic state), but also added external information (e.g., weather condition, holiday, the day of week, and the time of day) into the model, to construct more accurate prediction model. Zhu et al. (2021) presented a multivariate deep learning technique based on LSTM and multi-layer perceptron (MLP) for the dynamic prediction of traffic incident duration in urban expressways. This method integrates the traffic incident-related factors and real-time traffic flow to predict the traffic incident duration. Urolagin et al. (2021) developed a combined model of multivariate LSTM with Mahalanobis and Z-score transformations to forecast oil price. They considered historical data on West Texas Intermediate (WTI) oil prices as well as other factors affecting oil price to construct the multivariate LSTM model.

2.7. Our contributions against existing techniques

The main objective of this study is to address the blood donation/demand prediction problem based on a multivariate time-series deep learning approach. In this context wherein the time-series are complex as the trends and patterns change over time, deep learning techniques like LSTM are a viable alternative to more traditional methods such as ARIMA. Existing machine learning blood donation/demand forecasting methods are mainly based on direct using of historical time-series of the donation/demand, in lack of thorough analysis of external knowledge during the COVID-19 pandemic. The proposed multivariate LSTM time-series blood donation/demand model not only considers the past values of the donation/demand (internal features), but also takes into account time-series of the new confirmed COVID-19 cases and deaths (external features). Although this idea has been used in other tasks such as traffic prediction systems (Zhu et al., 2021; Zhu et al., 2021), it has not been used to predict the blood donation/demand values affected by the COVID-19 cases/deaths. By adopting the proposed multivariate time-series model for the blood donation/demand forecasting during the COVID-19 pandemic, a resilient blood supply chain management is achieved, capable of handling uncertain blood supply/demand.

3. Multivariate blood supply/demand forecasting model

In this study, we apply a two-stage BSC model as proposed by Shokouhifar et al. (2021), where there is only one blood center, i.e., TBC (Tehran Blood Center). Each demand node (hospital) is sourced by the TBC. The network includes a set of donor sites which supply the required blood products (platelet units) for the TBC. At every day, after processing and testing of the received platelet units, the TBC delivers the valid platelets to the different hospitals. At every day, each hospital faces uncertain demands for the different types of platelet ages to be satisfied. To efficiently manage the BSC, it is of utmost importance for the decision maker to know (predict) the supply/demand in the BSC at the next days. By outbreaking the COVID-19 pandemic, the uncertainties occurring in the BSCs in terms of both supply and demand have become more challenging. To effectively handle these uncertainties, we apply a multivariate forecasting model based on LSTM to predict the total supply in the TBC as well as the total demand of the different hospitals. LSTM is a recurrent neural network (RNN) based deep learning model, which was designed by Hochreiter & Schmidhuber (1997) to deal with sequence prediction problems. It is capable of remembering a sequence of data points for a long period when compared to traditional neural networks (Johny et al., 2022).

To efficiently forecast blood donation/demand during the COVID-19 pandemic, we design a multivariate LSTM time-series analysis, as there are interdependences between multiple factors affecting by the COVID-19 pandemic over time. The LSTM network contains an input gate, a forget gate, and an output gate to capture spatial–temporal correlation and dynamics of multivariate time-series data. The input gate is used to receive new information, while the forget gate is responsible for discarding information from the cell state. The output gate performs a sigmoid function to regulate the values and send the multiplied value out and to the hidden state of the next cell.

The proposed multivariate time-series approach for the blood donation/demand forecasting is shown in Fig. 2, which utilizes two multivariate LSTM models to forecast the total blood donation and demand for the next week. These two time-series forecasting models are named as Multivariate LSTM for DoNation (MLSTM-DN) and Multivariate LSTM for DeMand (MLSTM-DM). Each forecasting block is a multivariate model based on LSTM, which utilizes multiple historical data including 14-day time-series of the donation/demand (internal features) as well as 14-day time-series of COVID-19 cases/deaths (external features) to forecast the total donation/demand for the next week. Each multivariate block takes multiple variables (with their respective daily histories), as the future value of blood donation/demand not only depends on its previous values but also affected by outbreaking the COVID-19 pandemic. We use a many-to-one LSTM architecture which produces a single output based on processing of the sequences of three feature vectors. The output of the LSTM layer is mapped into regression layer using fully connected layers. To train the LSTM models, tanh activation function and Adam optimizer are used. The input data are scaled (using min–max scaler) going into the model and un-scaled coming out. Learning rate is set to 0.001, and MSE is considered as the loss function.

To verify the performance of the proposed model, we collected the historical data of the blood donation/demand as well as the new confirmed COVID-19 cases and deaths in Iran from February 24, 2020, to October 14, 2021. The total time interval includes 85 weeks. We consider 70 % (49 weeks) of the whole data from February 24, 2020, to April 13, 2021, to train the learning models (MLSTM-DN and MLSTM-DM), while the remaining 30 % (26 weeks) of the data from April 14, 2020, to October 14, 2021, were used to validate the generalizability of the trained models on the unseen test data. To justify the performance of

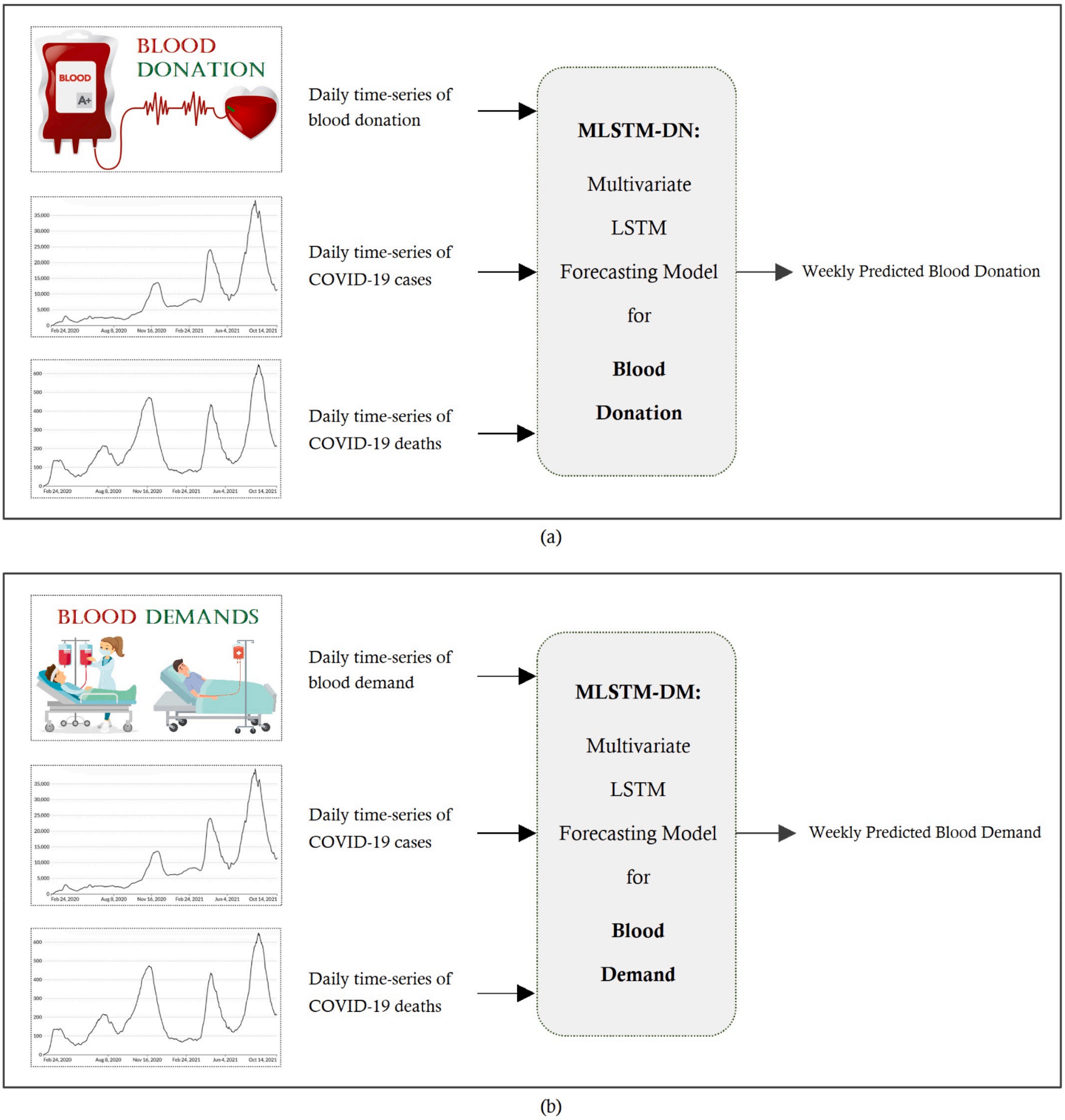

Fig. 2. Multivariate time-series LSTM models: (a) MLSTM-DN and (b) MLSTM-DM.

the trained models on the test data, the predicted donation/demand values are compared with the actual donation/demand values, in terms of mean absolute error (MAE), root mean square error (RMSE), mean percent error (MPE), and correlation factor (R), as.

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|P_i - A_i| \tag{1}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - A_i)^2} \tag{2}$$

$$\mathrm{MPE} = 100 \times \frac{1}{N}\sum_{i=1}^{N}\frac{|P_i - A_i|}{A_i} \tag{3}$$

$$\mathrm{R} = \frac{\frac{1}{N}\sum_{i=1}^{N}|P_i - \overline{P}| \times |A_i - \overline{A}|}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - \overline{P})^2} \times \sqrt{\frac{1}{N}\sum_{i=1}^{N}(A_i - \overline{A})^2}} \tag{4}$$

where P_i and A_i are the predicted and actual value of the demand/donation for i-th test week, respectively. Moreover, N is the number of test samples, i.e., $N = 26$.

4. Results

4.1. Blood data collection

The first confirmed positive case of COVID-19 in Iran was observed on February 19, 2020. By rapidly spreading the virus across the country, people were encouraged to observe social distancing and stay at home, and consequently, many public events were cancelled. Although these measures partially caused to prevent further spread of the virus, they faced Iranian Blood Transfusion Organization (IBTO) with a significant shortage in the blood products. As seen in Fig. 3, after two weeks following the COVID-19 outbreak, the total number of blood donations in Iran had reduced from 33,275 to 23,465 blood units, which shows a sudden drop of 29.4 %. By the COVID-19 outbreak, IBTO organized a national committee to manage the related concerns about the COVID-19 pandemic such as suitability of the donated blood units, safety of the

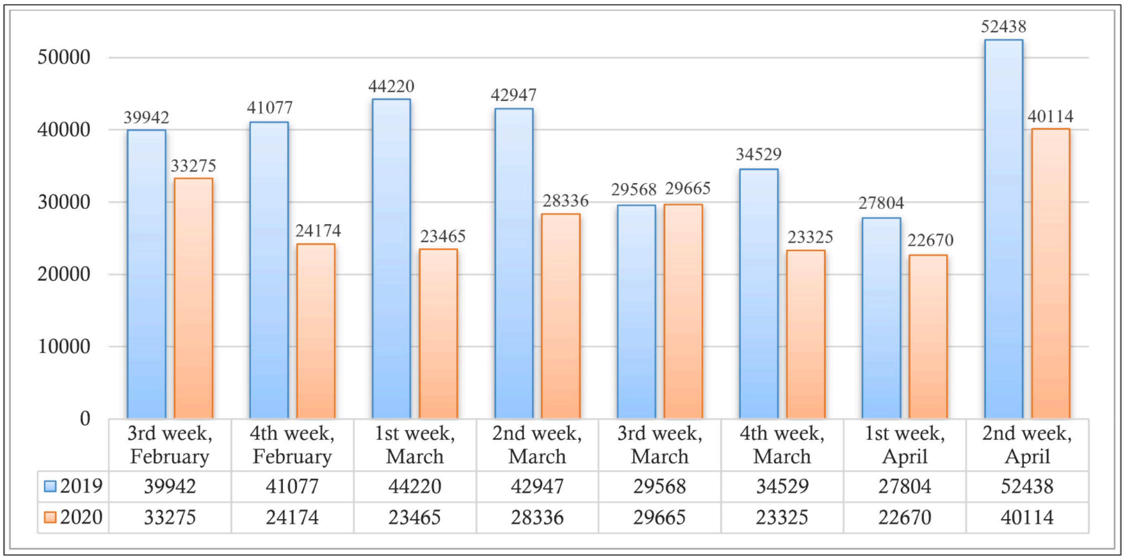

Fig. 3. Trend of the number of blood donation during 8 weeks following the COVID-19 outbreak in Iran.

staff in the blood centers, and compensating the emerging blood shortage (Maghsudlu et al., 2021). By the measures taken by this committee, the number of blood donations had increased from 23,465 in the second week of the outbreak to 29,665 in the fourth week of the outbreak, which resulted an increase of 26.4 % in the blood units. Typically, because of the Nowruz (new year) holidays in Iran from the third week of March to the first week of April, a 20–30 % drop in the total blood donations was observed every year before the COVID-19 pandemic. In the same period in 2020, the government adopted strict policies to force people staying at home, which resulted a significant drop in the number of blood donations. After the Nowruz holiday, the number of blood donations recovered again from 22,617 in the first week of April to 40,114 in the second week of April (77.4 %).

The gathered data in this paper includes the demands/donations from February 24, 2020, to October 14, 2021, in TBC. To understand the classification of the blood donors in terms of their gender and age, the data for 62,026 blood donors in the TBC from January 21, 2020, to April 9, 2020, are provided in Table 3. The data for the same period in 2019 shows total 78,326 donations, which results a drop of 20.8 % in 2020, due to the COVID-19 outbreak. The main concern of blood centers during the COVID-19 pandemic is to maintain a proper balance between production and demand. As mentioned above, at the beginning of the COVID-19 outbreak in Iran, a drop of 20.8 % and 29.4 % was observed in the donations of the TBC and IBTO, respectively. However, it was partially compensated by reducing the need for the unnecessary blood transfusions and canceling non-emergency surgeries. Although by resumption of the normal hospital surgeries, the demand was increased, the number of donations was also increased through the measures taken to compensate the shortage in blood products. As a result, from April to November 2020, compared to the same period in 2019, IBTO had around 7 % decrease in the total blood donations.

4.2. COVID-19 data collection

As mentioned above, not only time-series of the blood donation/demand is utilized as inputs of the learning models, but also they take the 14-day time-series of the COVID-19 cases/deaths to find the COVID-19 outbreak type. The number of daily new confirmed COVID-19 cases and deaths in Iran from February 24, 2020, to October 14, 2021, are provided in Figs. 4 and 5, respectively.

4.3. Results of donation/demand prediction

As mentioned above, the gathered data from February 24, 2020, to October 14, 2021, was split up into train data (70 %) and test data (30 %), using hold-out method. To capture the performance of the trained MLSTM-DN and MLSTM-DM models, Fig. 6 statistically qualifies them in term of the correlation between predicted and actual donation/demand values. The results clearly demonstrate that the proposed model is powerful in forecasting the blood donation and demand. Another point is that the correlation factor of the forecasted blood donation by the MLSTM-DN is better than the correlation factor of the forecasted blood demand by the MLSTM-DM, which means that the pattern of the donation can be learned better than the pattern of the demand.

To gain insight into the detailed results of the proposed model for the blood donation/demand forecasting, Figs. 7 and 8 provide the weekly forecasting error and percent error between actual and predicted values for the test data samples. The forecasting error and percent error for i-th test week ($1 \le i \le 26$) can be calculated as Eqs. (5) and (6), respectively. In these formula, A_i and P_i are the actual and predicted demand/donation for i-th test week, respectively. For better analysis of the obtained results in Figs. 6-8, the overall values of the performance measures on the train and test datasets are summarized in Table 4. The results show a little bit difference between the results on the train and test data, which demonstrate a proper generalizability of the proposed model to forecast unseen data samples in the test dataset.

$$ForecastingError_i = P_i - A_i \tag{5}$$

Table 3
Frequency of the blood donors in TBC from January 21, 2020, to April 9, 2020.

	Total	Age Groups						Gender	
		18–24	25–34	35–44	45–54	55–64	>65	Male	Female
Number of Donors	62,026	4,310	15,768	21,157	15,406	5,368	17	58,936	3,090
Contribution (%)	100	6.95	25.42	34.11	24.84	8.65	0.03	95.02	4.98

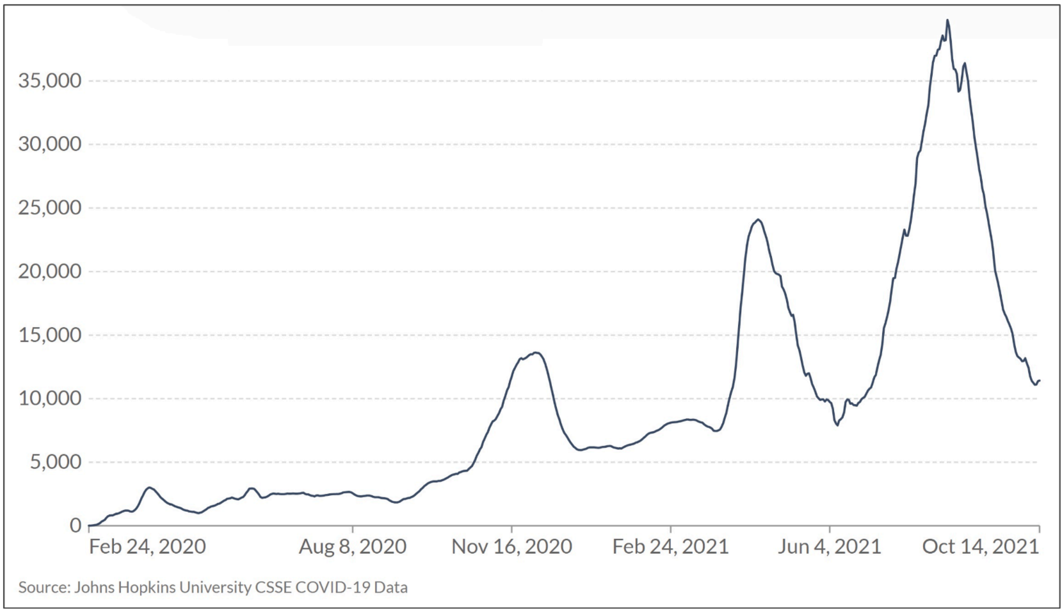

Fig. 4. Daily COVID-19 cases in Iran.

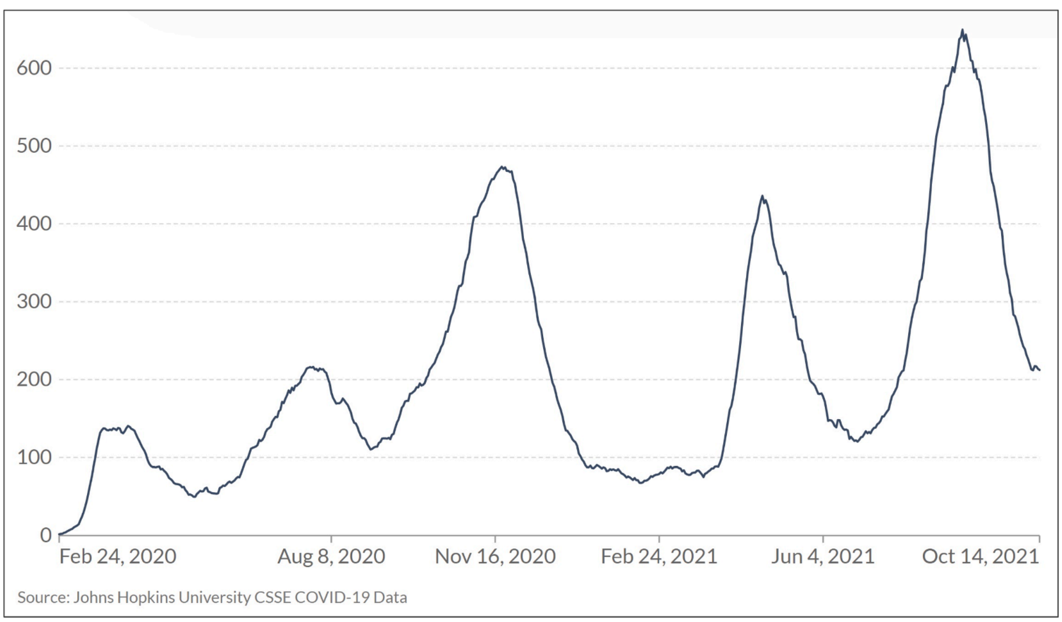

Fig. 5. Daily COVID-19 deaths in Iran.

$$PercentError_i = \frac{P_i - A_i}{A_i} \quad (6)$$

4.4. Results of inventory management

To justify the performance of the proposed blood donation/demand forecasting model against the existing uncertainty handling methods, we compared it against two inventory management models: a stochastic method based on genetic algorithm (Stochastic-GA) (Rajendran and Ravindran, 2019) and a fuzzy method based on whale optimization algorithm (Fuzzy-WOA) (Shokouhifar et al., 2021). In the proposed model, we utilize the same WOA algorithm as in Fuzzy-WOA model to optimize the BSC, but considering forecasted blood donations and demands rather than the fuzzy uncertainties. All algorithms were utilized for the inventory management of blood platelets for a 26-week time horizon from April 14, 2020, to October 14, 2021. The obtained results in terms of the shortage rate and wastage rate on average for 26 test weeks can be seen in Fig. 9, which clearly demonstrate the efficiency of the proposed model to reduce (on average) the shortage and wastage rates by 32.1 % and 26.6 %, respectively.

5. Conclusion

In this paper, a multivariate time-series model based on LSTM has been presented for the blood donation/demand forecasting and resilient BSC management during the COVID-19 pandemic. The proposed model takes into account more realistic values for the blood supply and demand, which can be used for the blood inventory management in the real-world BSCs. The obtained results of applying the proposed model for inventory management of blood platelets in Tehran Blood Center,

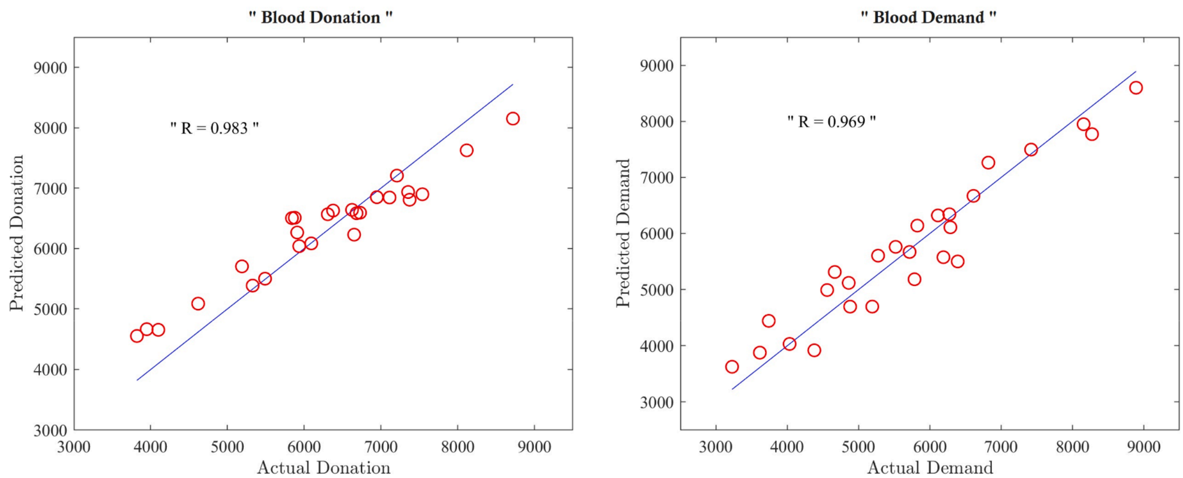

Fig. 6. Correlation between predicted and actual values of blood donation (left) and demand (right).

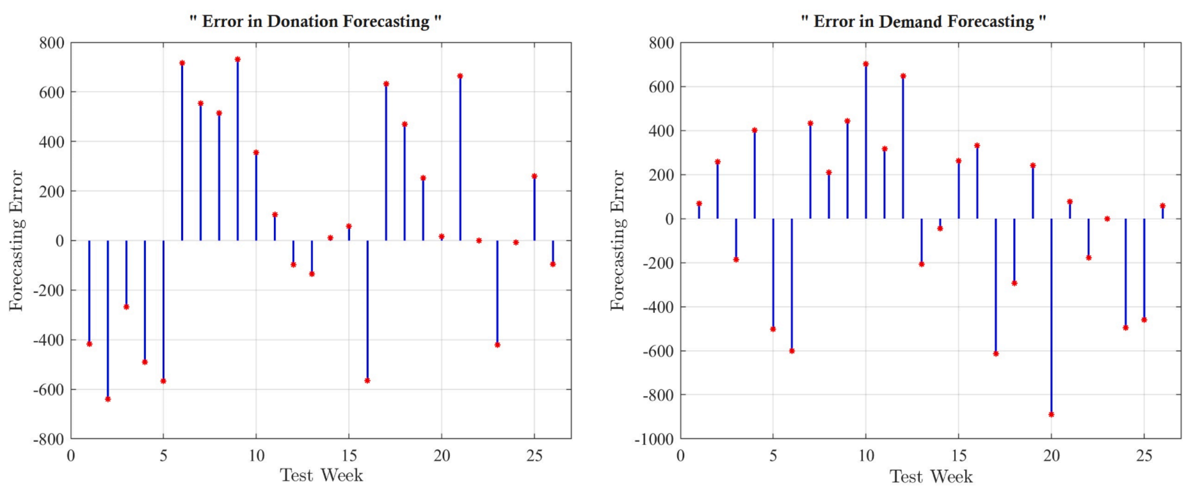

Fig. 7. Error analysis between predicted and actual values of blood donation (left) and demand (right).

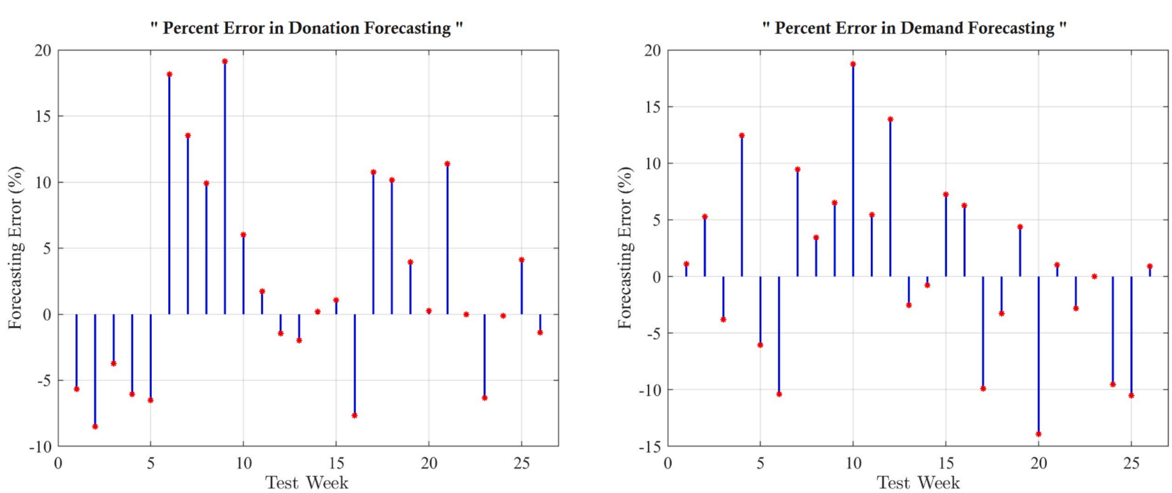

Fig. 8. Percent forecasting error for blood donation (left) and demand (right).

Iran, from February 24, 2020, to October 14, 2021, shows reduction in shortage and wastage rates against the existing methods by 32.1 % and 26.6 %, respectively. By efficiently forecasting the blood donation/demand especially at the pandemic peaks, the manager can decide about rescheduling elective surgeries, cancelling unnecessary surgeries, or shifting elective inpatient surgical cases to outpatient surgeries. The proposed model can be used to assist the blood supply chain decision makers to efficiently manage the supply/demand and prioritize the

Table 4
Comparison of different performance measures for donation/demand prediction on train and test datasets.

Measure	Donation (MLSTM-DN)		Demand (MLSTM-DM)	
	Train	Test	Train	Test
Mean Absolute Error (MAE)	277	348	306	343
Root Mean Square Error (RMSE)	341	425	362	409
Mean Percent Error (MPE)	4.3	6.1	4.8	6.5
Correlation (R)	0.989	0.983	0.984	0.969

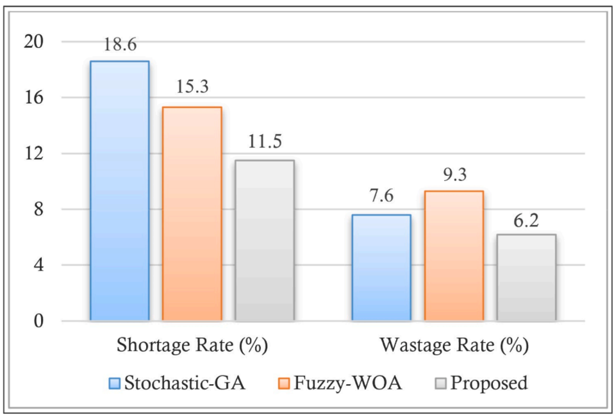

Fig. 9. Comparison of the different inventory management models in terms of shortage and wastage rates.

blood transfusion during the COVID-19 pandemic and similar public emergencies in the future.

In this paper, LSTM has been utilized as a multivariate time-series deep learning model for the blood donation/demand forecasting, considering internal features (daily time-series of the blood donation/demand) and external features (daily time-series of the new confirmed COVID-19 cases/deaths). As a future work, different timely periods for the input internal/external features (rather than daily time-series) and output (rather than weekly forecasting) would be evaluated. As another future work, other external information such as vaccination condition, holiday, and time of month or year, would be added into the model, in order to construct more accurate prediction model. In this study, we have utilized LSTM to construct the multivariate time-series model. In future, other machine learning time-series approaches such as ANFIS, support vector regression, decision trees, feedforward neural networks, and radial basis functions, can be applied for the multivariate time-series blood donation/demand forecasting.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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